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Masked Face Recognition Using FaceNet Algorithm

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***Abstract* - In the past three years, the entire world has been exposed to a new virus, COVID-19. It has become very difficult to deal with the fingerprint system, as the exchange of things and contact with devices by more than one person is a good way to transmit the virus. Accordingly, many institutions and organizations have resorted to using face prints as an alternative to handprints to identify people and record the attendance of employees in general. Since the virus is a virus that infects the respiratory system, people are forced to wear face masks or the so-called masks to avoid transmission of the virus during coughing by the infected person. Since the wearing of masks greatly affects the facial features, it was necessary to come up with a technology that allows the identification of masked faces, and this is the subject of our study. Since the face loses many of its features while wearing masks, an algorithm was proposed to recognize the face and train the convolutional neural networks (CNN) through some of the main facial features, including 3D imaging, as it was concluded that the triple loss does not apply to our data sets, as 3D selection has less loss compared to 2D image, Due to its ability to select all feature samples from feature spaces with larger distances between layers and reduced distances between regions, a large cosine loss was utilized as the training loss function. In order to reach a model that deals more with areas not covered by the mask, the input unit was designed, as its function is to combine the Inception- Resent unit and the Convolutional Mass unit, and so, any portion of the face that isn't covered gains weight, thus increasing the importance of those areas in the recognition of masked faces, and experiments that were conducted on several sets of masked faces data showed that the algorithm works to significantly increase the accuracy of masking face recognition, and it can accurately recognize the face using masks.**

Keywords: Masked face detection, Convolutional Neural Network (CNN), face Net algorithm.

I. INTRODUCTION

The face is one of the most significant stimuli in our surroundings since it communicates many essential aspects of the person, including identity, feelings, emotions, age, gender, and many others. Numerous studies have demonstrated the detrimental impacts of masks, including the inability to recognize identity and feelings. This study opens up new possibilities for how face masks affect facial recognition. Medical masks slow down and inaccurately classify faces [1].

Face detection systems have been mainly built based on the eyes, nose and mouth, as these features are suitable for unmasked faces. While under special circumstances represented by epidemics and viral laboratories, which require the presence of masks that partially hide the face, it requires studying and understanding the methods of identifying the masked face. Several algorithms have been proposed to detect both masked and unmasked faces [2].

Determining whether a face is obscured, or "masked face detection," the majority of contemporary techniques have been presented. Even while preserving lives is important, there is a pressing need to identify those wearing masks without having to divulge who they aren't. People frequently present to cameras in public spaces such building entrances and immigration checkpoints, which presents the issue the areas covered are essential for face detection and recognition of face [3].

As masked face recognition is utilized in numerous applications, including safe authentication and the monitoring of individuals wearing face masks, it has been discovered that research in this area has grown rapidly over the past few years. However, there isn't a single generality for the development and assessment of the algorithms, data sets, and methodologies suggested in works dealing with masked faces. Additionally, a variety of artificial neural network techniques for identifying and distinguishing mask-wearers are quite helpful [4].

II. THEORETICAL BACKGROUND

1) Convolutional Neural Network

The convolutional neural network (CNN) shown in figure (1) is one of the most effective neural networks, which has demonstrated its excellence in several applications, including ima.ge classification, discrimination, recovery and facial recognition. To manage the amount of transformation, scaling, and distortion, CNNs frequently consist of several subsequent layers, including fully linked input, convolution and partial

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reduction layers, and output layers. They are capable of effectively learning various interclass variances from training data, including age and facial expressions.

Numerous face data sets have been utilized to train CNN-based algorithms [5].

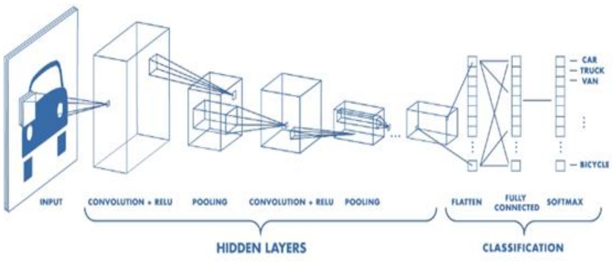

Figure 1: CNN architecture [6]

AlexNet[7] is one of the most well-liked ready-made structures that has been used in FR missions. Even when the data sets are scaled, AlexNet has improved training efficiency and decreased mistakes thanks to integrated graphics processing units (GPUs). Additionally well-known CNN-based algorithms, VGG16 and VGG19 have been applied to a variety of computer applications, including facial recognition [8]. Typically, Convolution-based characteristics or representations are permissible in VGG-based models. Despite the astounding accuracy obtained, there is a struggle in terms of training time and complexity.

Due to technological progress, the task of image recognition has become more difficult, and thus deeper neural networks are used. Whereas, adding more layers to networks makes training more complex and difficult; This causes precision decay. The leftover network (ResNet), which adds more layers and delivers higher accuracy, was introduced to address this issue [9]. Complex features can be identified by newly additional layers. For FR tasks, MobileNet is a very significant and compact deep neural network that is mostly built on streamlined design. Its architecture displayed exceptional hyper parameter performance, and model calculations were quicker [10].

2) Face Net Algorithm

The FaceNet algorithm is one of the most important algorithms used to recognize masked faces. This method was introduced, which uses a single deep neural network as its foundation to identify faces. The algorithm (Face Net) for learning mapping from face photos comprises of three fully connected (FC) layers with more than (140) million parameters and eleven convolutional layers (M). Figure (2) depicts the framework's overall layout (Face Net) [11].

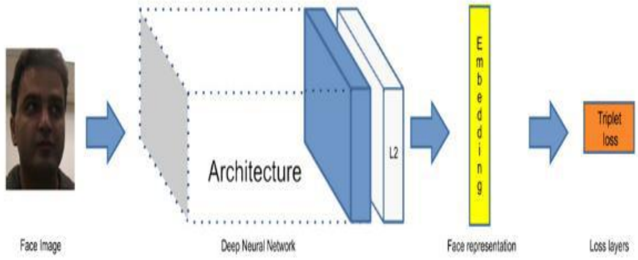

Figure 2: Overview of the framework (Face Net)

It feeds a deep learning network with data from a pre-trained FaceNet model. Where an extremely deep CNN is paired with a batch layer and FaceNet. L2 normalization supports Deep CNN. The outcome of this normalization is the inclusion of the face. Face embedding is followed by triple loss during training. Identity alignment causes the triple loss to have the lowest value. [12].

The network should be set to anticipate a significant boost to the task of recognizing and verifying faces. We retrain the FaceNet model using a very large number of masked and unmasked face photos.

a) Mask detection

Face masks, which come in a variety of sizes, colors, and shapes, are now some of the most widely used cosmetics for masking facial features. To accurately detect masks, deep learning networks need more rigorous training [12]. In the mask detection task, the majority of the current detection techniques—which are often researched for object detection—are tweaked and researched. Classifying object proposals is the main use of the deep ConvNet. In the realm of congested faces, R-CNN applies a selective search technique, simply giving them to Convolutional neural networks , you can extract thousands of facial regions that are currently among the most popular, and creates a feature vector for each region [13].

The application of hash-based deep networks for mask discovery has been extensively studied. Using semantic hashing, a complete convolutional neural network (FCN) is constructed.

III. METHODOLOGY

1) Dataset Preprocessing

It is challenging for the model to learn to map features when the face is covered by a mask because there aren't any datasets for masked-faces, which reduces the recognition rate. We also know that deep learning networks often require large and diverse data sets for training. This issue was fixed by developing a dataset using an algorithm that produced

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convincing images of the face based on identification of significant facial features. For the purpose of training the model, the dataset of shoulder pain called (UNBC-McMaster shoulder pain) was used, where masks were added using Python language, and realistic images of the masked face were produced using face detection, key feature detection, and mask coverage analysis. [14].

Convolutional neural networks (CNN) were utilized for preprocessing, and only one image with faces was obtained, which was then used for face detection. When attempting to recognize important features, CNN can only distinguish the prominent features of the ey.es, no.se, both the left and right mouths. Because it is challenging to produce a practical representation of a masked face using only these five key points, we applied HOG features to recognize 68 prominent facial features. The approach reveals the essential ideas in more depth [12].

The relative positions of the chin and nasal bridge were utilized to calculate distance and structural information, generate mask coordinates, cover the face using standard mask templates (KN95), and create an image of the masked face. To create a more realistic image of the masked face, a frontal a picture of the mask, an analysis of the corresponding positions of the important spots on the face, and mask deformation all came into play [15].

2) Dataset Reduction

A technique for extracting the key elements, Independent component analysis is a technique for extracting components from multivariate (multidimensional) statistical data. ICA looks for statistically independent components, which sets it apart from other approaches. The basic concepts, applications, and estimation principles of ICA are briefly explained [16].

To derive algorithm (ICA). An algorithm can be classified by Bell and Sejnowski, and an interpretation of their algorithm can be provided as a method for maximum likelihood estimation [17].

Assuming that the distribution of each source (S_j) is given by the density (P_s),and the joint distribution of the sources (S) is given by [18][19].

$$(S) = \prod_{j=1}^{d} p_s(s_j) \ldots\ldots\ldots\ldots (1)$$

It is noted that by modeling the co-distribution as a product of the margin, the assumption that the sources are independent is taken. Using the special formulas from the previous section, this indicates the following density on $x = As = W^{-1}$.

$$P(S) = \prod_{j=1}^{d} p_s(w_j^T x).|W| \ldots\ldots\ldots (2)$$

All that remains is to determine the density of the individual sources (p_s), and given a real random variable (z), the cumulative distribution function *(cdf)F* is defined by:

$$F(z_o) = Pz(\le z_o) = \int_{-\infty}^{z_o} p_z(z)dz \quad \ldots\ldots (3)$$

Density is the derivative of *(Cdf)*.

$$_z(z) = F'(z) \ldots\ldots\ldots\ldots (4)$$

Thus, to specify a density for $(s_i s')$all you have to do is select some (cdf) for it. (cdf) should be a monotonic function that increments from zero to one, and what will be chosen as a reasonable "default" *cdf*file that slowly increments from (0) to (1), is the following sine function:

$$gs(\ ) = \frac{11}{+e^{-s}} \ldots\ldots\ldots (5)$$

Where,

$$p_s(s) = g'(s) \ldots\ldots\ldots (6)$$

The square matrix (W) is the parameter in the chosen model. Given a training set $\{x^{(i)}; i = 1, \ldots\ldots\ldots, n\}$, the log probability is given by:

$$\ell W(\ ) = \sum_{=1}^{ni} \left(\sum_{j=1}^{d} \log g'\left(w_{jT} x^{(i)}\right) + \log W\right) \ldots (7)$$

In order to increase the weight of this in terms of (W). Derivatives are taken and using the fact (from the first set of observations) that $\nabla_w|W| = W|W|(\ ^{-1})^T$, and the rule of learning random gradient ascent is easily done. For the $x^{(i)}$ training example, the update rule is:

$$W := W + \alpha\left(\begin{bmatrix} 1 - gw2\ {}_1^T x^{(i)} \\ 1 - gw2\ {}_2^T x^{(i)} \\ \vdots \\ 1 - gw2\ {}_{dT} x^{(i)} \end{bmatrix} x^{(i)T} + (W^T)^{-1}\right) \ldots\ldots (8)$$

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Where (α) is the learning rate. After the algorithm converges, $S^{(i)} = Wx^{(i)}$ is then calculated to restore the original sources.

By using (ICA) algorithm, we reduce the feature from (512) to (32) feature only.

3) Loss Function

Face Net is an algorithm for recognition faces developed by the team at Google that focuses on triple loss for model training. The model consists of three samples *(x^a, x^p, x^n)*, where *(x^a, x^p)* are two images of the face with the same identity (positive pair) [20], where *(x^a, x^n)*are two different representations of the same face (negative pair). Suppose that the *(x^a, x^p, x^n)* mappings in the feature space are, respectively, *$f(x^a)$, $f(x^p)$, $f(x^n)$*. The following equivalence can be employed by the non-distinguishing the feature distance of a single identity image smaller than several identities pictures' typical distances:

$$\|f(x^a) - f(x^p)\|_2^2 + \alpha < \|f(x^a) - f(x^n)\|_2^2 \ldots\ldots\ldots\ldots (9)$$

Where the area between the positive and negative pairings is shown by (α). Using the equation above, the advantage because the assignment of the same identity in the feature space is closer and the assignment of different identities is farther away, the distance between the positive pair can be made to be much less than the advantage distance between the negative pair [21]. Then the triple loss is as follows:

$$L_t = [\|f(x^a) - f(x^p)\|_2^2 - \|f(x^a) - f(x^n)\|_2^2 + \alpha]_+ \ldots\ldots (10)$$

A semi-rigid technique is often employed since choosing two photos that are extremely similar to selecting the two photos that are the most dissimilar will probably lead to training failure since the positive pair will make it harder for the model to obtain an accurate representation of features. This is because the network selects those triads that are valuable for training as much as possible. A positive pair is created by choosing two photographs with low similarity, whereas a negative pair is created by choosing two images with high similarity [22]. This approach is more balanced and has a faster rate of pattern repetition than the exact selection of photos for a triplet configuration with the greatest or least amount of variance.

4) Attention Model

The majority of the traits are hidden after using the mask, as can be seen from the characteristics of the masked face photographs. These useful traits are disregarded if the model continues to concentrate on the characteristics of the big image. By incorporating the network with a Convolutional Attention Module (CBAM) mechanism, the model can concentrate on the properties of the truly useful image, that is, the properties of the regions not covered by the mask [23].

The attention channel unit and the spatial attention unit are the two primary components of the convolutional attention unit, a technique for focusing attention based on convolutional neural networks. An attention chart is created by determining the feature data for these two units, and the output features are then obtained by multiplying the output features by the attention mapping and feature mapping. For output ($F \in R^{C\times H\times W}$) starting with any convolutional layer, CBAM can gen erate one-plot of dimensional channel attention $M_C \in R^{C\times 1\times 1}$and two-dimensional spatial attention mapping $M_S \in R^{1\times H\times W}$, similarly to equations (11) and (12), where ⊗ is the combination of the element and (F'') is the final output feature designation [24].

$$F' = M_C(\mathrm{F}) \otimes \mathrm{F} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

$$F'' = M_C(F') \otimes F' \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

5) Network Structure

The core network that we used was Inception-ResNet-v1. In Figure (3), the network architecture is displayed Miniaturization and Inception-ResNet modules make up the majority of Inception-ResNet-v1. While shrinking the size of the feature map, the minification module extracts features using a parallel architecture. The aggregation over the residual connection is replaced by the Inception-ResNet module, and the feature map size transformation is canceled. The model incorporates elements from several scales, alludes to the concept of multi-scale approaches, and includes wrap beads of various sizes to broaden the model's receptive field [25].

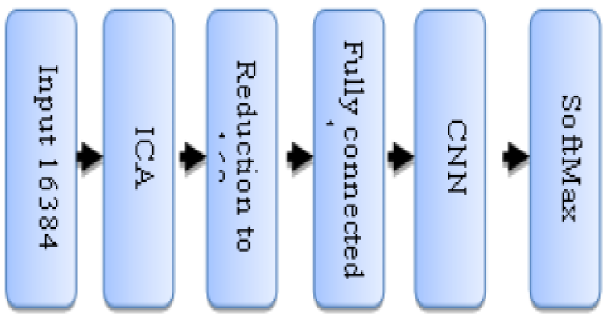

Figure 3: Network

IV. RESULTS

A few tools are required to evaluate machine learning algorithms after they have been applied. Performance

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measurements are the name of these instruments. The studies have incorporated a huge variety of measures, each of which considers various facets of the algorithm's performance. Therefore, it calls for a suitable set of metrics to assess performance for each machine learning issue. In this study, various widely used classification problem measures were used to gather insightful data on algorithm performance and conduct a comparison analysis. Accuracy, recall, F1 score, and confusion matrix make up these scales [26][27].

Precision: It merely displays "how many picked relevant data pieces." To put it another way, how many of the observations that the algorithm predicted would be positive actually were.

The precision is calculated by dividing the total number of true positives by the sum of all true positives and false positives, as shown by equation (13).

$$precision = \frac{T_P}{T_P+F_P} \text{ .... (13)}$$

From Figure (4), we note that the evaluation validity rate has reached (1).

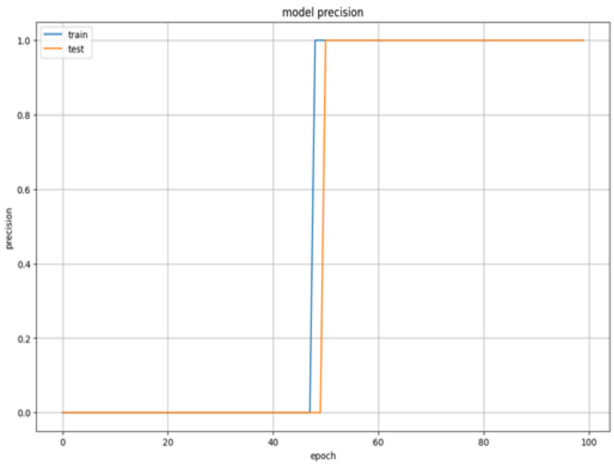

Figure 4: Precision chart

Sensitivity (Recall): Provides "the number of selected relevant data elements". Indeed, among the actually positive feedback, how many were predicted by the algorithm. According to equation (14), retrieval is equal to the number of true positives divided by the sum of true positives and false negatives:

$$Recall = \frac{T_P}{T_P+F_N} \text{.............................. (14)}$$

From Figure (5), we notice that the sensitivity of the network has reached (0.7862).

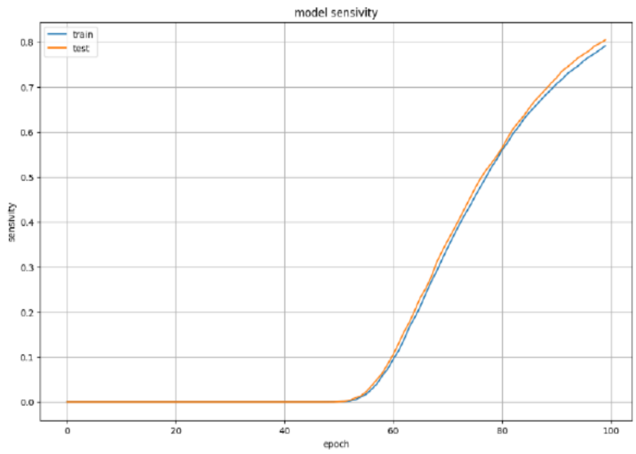

Figure 5: Recall chart

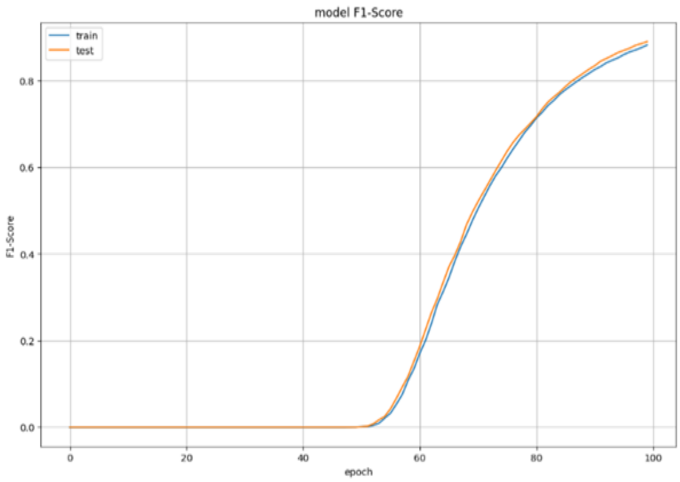

Figure 6: F1-Score chart

F1-score: This statistic, commonly known as f-score or f-measure, calculates algorithm performance by accounting for accuracy and recall. It is the harmonic mean of memory and accuracy in mathematics, written as.

$$F1-score = 2 \times \frac{precision \ \times Recall}{precision \ + Recall} \text{ .... (15)}$$

From Figure (6), we notice that the harmonic mean of the evaluation's validity and sensitivity reached (0.8784).

Accuracy: It is the most popular and most likely the first option for assessing how well an algorithm performs in classification problems. It can be characterized as the proportion of correctly identified data items to all observations as shown in equation (16). Despite its widespread ease of use, accuracy is not the most appropriate performance measure in some situations, especially in cases where the target variable groups in the data set are unbalanced.

$$Accurcy = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \text{ .... (16)}$$

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From Figure (7), we notice that the percentage of accurately classified data items has reached (0.9723).

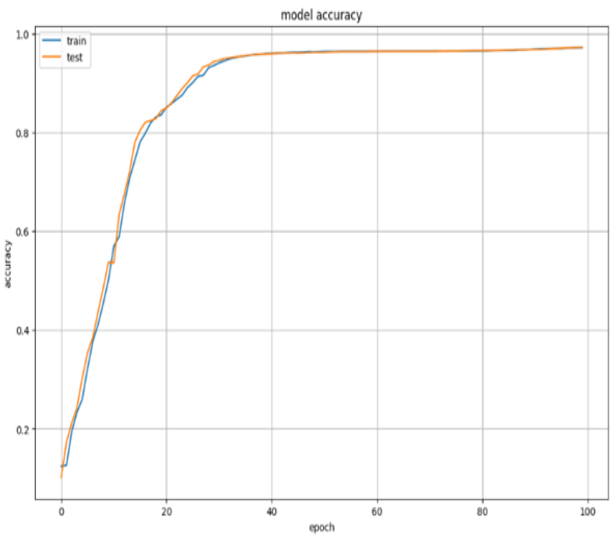

Figure 7: Accuracy chart

Confusion Matrix: One of the simplest descriptive metrics for determining a machine learning algorithm's validity and accuracy is this matrix. Its primary application is in categorization issues when the output can have two or more different class kinds. Using Figure (8), we note that the highest value obtained from the correct test data was (2824) out of the total data of (39089).

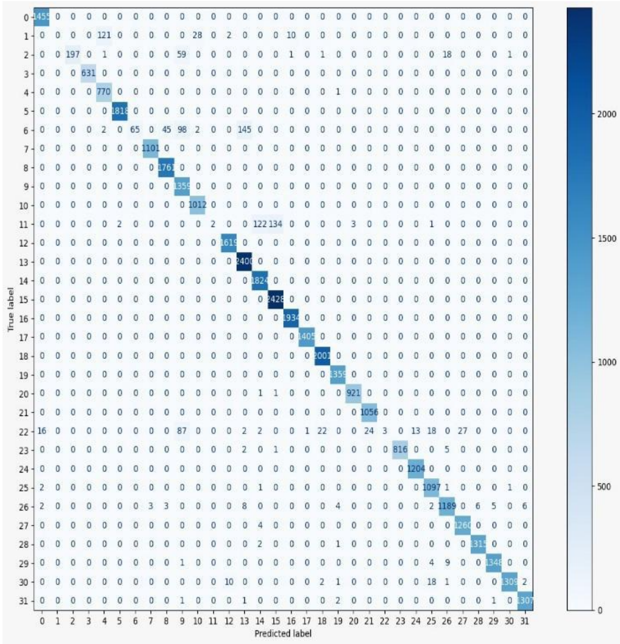

Figure 8: Confusion Matrix

V. COMPARING THE RESULTS WITH PREVIOUS STUDIES

The following table shows a comparison of the results of the current study with the results of some studies conducted in other countries on the topic of revealing masked faces.

Table 1: Related works Comparison

Researcher's name and year	Dataset	Technique used	Accuracy %	Ref
(Marinez, 2002)	AR-Face Database	Transfer learning PCA	85.70	[28]
Sun et al. (2013)	LFW	Hybrid ConvNet-RBM	93.83	[29]
Guo et al. (20.17)	LWF	Deep Face based on DNN using VGG Net	97.35	[30]
Y. Sun et al. (2014)	LFW	DeepID	97.45	[31]
Y.u et al. (20.17)	YTF	BQ A method based on CNN	99.01	[32]
O. M. Par.khi et al. (20.15)	YTF	Deep CNN	98.95	[33]
Y. Taigman et al. (20.14)	YTF	Deep Face system	97.35	[34]
Y. Zhang (20.15)	ORL	Global +ACNN local Expansion	93.30	[35]
S. Guo et al. (20.17)	ORL	CNN + SV.M	97.5	[30]
H. Hu et al. (20.17)	ORL	CNN-2	95	[36]
J. Cai et al. (2015)	FEI face	Sparse representation face recognition	61.31	[37]
Present study	UNBC-McMaster shoulder pain	CNN-ICA	97.23	-

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The results and discussion may be combined into a common section or obtainable separately. They may also be broken into subsets with short, revealing captions. This section should be typed in character size 10pt Times New Roman, Justified.

VI. CONCLUSION

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ACKNOWLEDGEMENT

The results of the tests show that the implemented system is capable of producing a superior classification of facial images and features in comparison to other standard models, as this method produced quick and accurate despite the fact that 50% of faces used were hidden by face masks (MaskTheFace), which can be used to mask faces. This results in the creation of a large data set of masked faces.

The possibility of employing the ICA algorithm used in signal processing to classify and detect faces. In the proposed model for (ICA), a high data reduction was achieved, while the high accuracy of (160) out of the original (16384) was still achieved.

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